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Feature Analysis for Motor Imagery EEG Signals with Different Classification Schemes

Esra KAYA *[1], Ismail SARITAS[1]

Abstract

A Brain-Computer Interface (BCI) is a communication system that decodes and transfers information directly from the brain to external devices. The electroencephalogram (EEG) technique is used to measure the electrical signals corresponding to commands occurring in the brain to control functions. The signals used for control applications in BCI are called Motor Imagery (MI) EEG signals. EEG signals are noisy, so it is important to use the right methods to recognize patterns correctly. This study examined the performances of different classification schemes to train networks using Ensemble Subspace Discriminant classifier. Also, the most efficient feature space was found using Neighborhood Component Analysis. The maximum average accuracy in classifying MI signals corresponding to right-direction and left-direction was 80.4% with a subject-specific classification scheme and 250 features.

Keywords: BCI, classification scheme, eeg, feature selection, subject-specific, subject-independent

1. INTRODUCTION

Everything that occurs with the transfer of information through different mediums occurs in the communication field. In human physiology, the main communication organ is the brain. In realizing any function, the first message emerges in the brain as electrical signals and is transmitted to the whole body through neurons. Functions can be performed without body parts if the electrical signals arising from the messages formed in the brain are measured and decoded [1]. Brain-Computer Interface (BCI) systems replace the place of neurons by directly transferring information from the brain to external devices [2]. Electroencephalogram (EEG) is the technique BCIs generally use to measure electrical signals of the brain because it is non-invasive and harmless and can be portable and low-cost. Thus, BCI can decode EEG signals for different brain activities [1]. BCI technology can provide many applications, especially for people who suffer from stroke, spinal cord injury, amyotrophic lateral sclerosis, or are amputated, by helping them to control external devices such as wheelchairs and robotic arms [2, 3]. BCIs can also improve healthy people's quality of life by assisting them in different activities. Decoding the

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movement intention from the brain is essential to control an external device. EEG signals generated in response to movement intentions are called Motor Imagery (MI) signals [3]. Due to the noisy nature of EEG signals (environmental noise, Electrocardiography (ECG), Electrooculography (EOG), and Electromyography (EMG)), it is hard to discriminate the class samples [1, 2]. Thus, it is important to choose the best classification scheme to train a network and to determine the most efficient feature space.

If we examine the literature studies using different classification schemes, Zhu et al. proposed a CNN structure based on CSP to preserve temporal information for the subject-specific scheme. They obtained 73.0% for right-hand and left-hand MI EEG signals of 25 healthy subjects between the ages of 18 and 25 [4]. In another study, Xu et al. used VGG16 CNN architecture as a transfer learning method for the subject-specific classification of right-hand and left-hand MI EEG signals of 9 subjects. They have used the STFT output spectrogram of the signals as inputs for the CNN. The obtained mean accuracy was 74.2% [5]. Zhao et al. used a multi-Branch 3D CNN architecture for subject-specific classification of right-hand and left-hand MI EEG signals of 9 subjects. The 3D input of the CNN was the signals' time steps with the electrode positions where zero value was used for the nonexistent electrodes. The average accuracy was %75 [6]. Ha and Jeong proposed a Capsule Network for a more robust subject-specific classification of right-hand and left-hand MI EEG signals obtained from 9 subjects. They used spectrograms of the STFT method as inputs and obtained a 77.0% average accuracy [7]. Jin et al. aim to control the complexity of the Extreme Learning Machine (ELM) network model by excluding redundant hidden neurons using sparse Bayesian learning for the subject-specific classification of right-hand and left-hand MI EEG signals of 9 subjects. The obtained mean accuracy was 78.5% [8]. Kwon et al. generated a new input based on spectral-spatial filtering using mutual information for a CNN structure with a feature fusion process to develop a calibration-free BCI system. The data belong to 54 subjects of right-hand and left-hand MI EEG signals. They obtained 74.2%, and 71.3% mean accuracy for subject-independent and subject-specific classifications, respectively [9]. Zhang et al. tried a deep CNN architecture for subject-specific, subject-independent, and subject-adaptive classification schemes by adapting the network parameters on different levels. They obtained 63.5%, 84.2%, and 86.8% accuracies with the related schemes for the right-hand and left-hand MI EEG signals of 54 healthy subjects between 24 and 35 years of age [10]. Perez-Velasco et al. proposed a new CNN structure called EEGSym, which employs the use of inception modules and residual connections for the Subject-Independent classification of right-hand and left-hand MI EEG signals. They used the mid-sagittal plane of the brain as the symmetry line. They obtained 84.7% mean accuracy for 54 subjects [11]. Dolzhikova et al. proposed a Multi-Subject Ensemble Deep CNN (MS-En-CNN) approach for the subject-independent classification of right-hand and left-hand MI EEG signals of 54 subjects based on trial sessions. They achieved an 85.4% average accuracy with the offline and online phases of session 2 [12].

There are also feature extraction and analysis studies for a BCI to recognize patterns in EEG signals more effectively. In a study realized by Raza et al., a method was proposed called Transductive Learning with Covariate Shift Detection (TLCSD) to detect covariate shifting in the distribution of features between training and testing phases of right-hand and left-hand MI EEG signals. The average mean accuracy was 74.92% for nine subjects [13]. Xie et al. proposed an algorithm for classifying right-hand and left-hand MI EEG signals by employing sub-manifold learning of multidimensional

Riemannian space of symmetric positive-definite covariance matrices called Tangent Space of Sub-Manifold (TSSM). The method gives a 75.5% mean accuracy for nine subjects with a Linear Discriminant Analysis (LDA) classifier [14]. Sakhavi et al. used the Filter Bank Common Spatial Pattern (FBCSP) method to extract temporal features of right-hand and left-hand MI EEG signals as inputs to the CNN architecture. They realized the classifications with three different scenarios for CNN: convolution only over time, convolution only over channels, and convolution over both time and channel. They obtained a maximum average accuracy of 74.5% for nine subjects using convolution over time and channel [15]. Fu et al. proved that mu rhythms are more effective for the binary classification of MI EEG signals using CSP features and a regularized LDA (RLDA) classifier. The average accuracy was 77.0% for seven subjects [16]. You et al. used a Flexible Analytic Wavelet Transform (FAWT) to obtain time-frequency features. They reduced the feature space dimension using Multidimensional Scaling (MDS) to classify four subjects' right-hand and left-hand MI EEG signals. The average accuracy was 85.3% [17]. Liang and Ma proposed a Multi-source Fusion Transfer Learning (MFTL) based on covariance matrices of Riemannian space to choose features of source subjects similar to the current subject. Thus, the features of the BCI system are always calibrated. They obtained 72.5% accuracy for the right-hand and both feet MI EEG signals of 12 subjects [18].

As seen from the literature, there are many studies about feature extraction and analysis studies to improve the classification of EEG signals. The studies show that there is still a need for improvement. However, the studies about the classification schemes generally belong to the subject-specific scheme, which is used without determining the best classification scheme. In this study, we have used four classification schemes to determine which scheme yields the best performance on our data. We evaluated the BCI-dependent scheme, which there is no study we have come across, as well as subject-specific, subject-independent, and subject-adaptive. Also, we determined the more efficient minimum feature space through several procedures to classify right-direction and left-direction MI EEG signals.

2. MATERIAL AND METHODS

2.1. Dataset

We obtained MI EEG signals related to the movements to the right and left direction from five healthy subjects. Before the recordings, necessary ethical permissions and informed consent forms were obtained. The signals were recorded in one session with two runs with a short break between them. The demographic properties of the subjects are given in Table 1.

Table 1 The demographic properties of the subjects EEG recordings belong to.

Subject	Gender	Age	Total Samples	BCI Training
S1	Female	37	160	Yes
S2	Female	26	160	No
S3	Male	22	80	No
S4	Male	52	80	No
S5	Female	33	80	No

The EEG signals were obtained using a 14-channel Emotiv Epoc+ headset. The sampling frequency was adjusted to 256 Hz. The advantage of this EEG headset is that it allows the user to realize cognitive tasks outside a medical facility, making it more suitable for daily use. The study paradigm was created using PsychoPy software, which works with EmotivPRO synchronously. EmotivPRO does not allow us to label signal epochs by itself while obtaining EEG signals. However, PsychoPy makes it possible to label the epochs of the EEG signal.

The paradigm starts with a 10s blank screen where the subjects look at it while not doing anything to create the baseline signal of the study. Then, a 2s part with a cue starts with a ding sound, which shows the right or left direction MI task with a command of direction. After the cue part, the subjects think of the movement associated with the command of the direction for 5s with a fixation cross appearing on the related direction of the screen. The trial ends with a ding sound, and the subjects close their eyes to rest until another ding sound starts. The paradigm is based on thinking of the movement in the desired direction, not on thinking of the movement of a limb. The timing of the cue-guided paradigm of the study is shown in Figure 1.

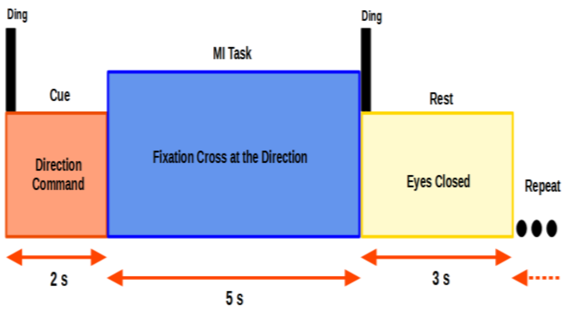

Figure 1 The BCI paradigm of the study.

2.2. Preprocessing and Feature Extraction

The signals were filtered with a 50 Hz Notch filter to eliminate the power noise. Common Average Reference (CAR) was applied for signal-to-noise optimization. Also, we used baseline correction to retract the signal distribution around the 0 amplitude position to ensure consistency among the signals. The 3% minimum and maximum outliers of the signals were discarded. Finally, the epoch signals related to the MI task were extracted. The baseline signal, where the subject does not realize any cognitive task, was subtracted from the epochs obtained from frontal lobe channels AF3, F7, F8, and AF4. Normally the frequency range preferred for EEG signals is 8-30Hz, corresponding to Alpha and Beta wavebands [19]. However, there are opinions out there that Delta and Theta bands can be used for control applications which are generally realized using MI EEG signals [20-23]. Also, while gamma wavebands can be confused with muscle activity, they can represent sensory processing, movement control, memory, and attention besides emotions [24]. Thus, we filtered the signals between 0.5 and 100 Hz using a bandpass filter.

Table 2. Feature list used in the study.

Feature Types	Features	Statistical Measures
Time	Signal Amplitude	Mean, Standard Deviation, Skewness, Kurtosis, Entropy
	TK Energy Operator	
Frequency	PSD	
Time-Frequency	WD	
	VMD	
	HHT	
Nonlinear	HE	-
	MSE	
	DFA	
	CD	
	Hjorth params	

After preprocessing, time, frequency, time-frequency, and nonlinear features of EEG signals belonging to four channels were extracted. Statistical measurements of signal amplitudes and Teager-Keiser(TK) energy values: mean, standard deviation, skewness, kurtosis, and entropy values form the time properties of signals. Statistical measures of the signal’s Power Spectral Density (PSD) values were extracted for frequency features. Wavelet Decomposition (WD) [25], Hilbert-Huang Transform (HHT) [26], and Variational Mode Decomposition (VMD) [27] methods were applied to the signals to obtain time-frequency features. Finally, the nonlinear features of the signals were extracted to define irregularities and long-range dependencies because of the EEG signals’ nonlinear nature. Hurst Exponent (HE), Detrended Fluctuation Analysis (DFA), Multiscale Sample Entropy (MSE), Correlation Dimension (CD), and Hjorth Parameters are the extracted nonlinear features [28-30]. The total feature amount was 844 for four channels: 40 time features, 140 frequency features, 620 time-frequency features, and 44 nonlinear features. The features used in this study to represent MI EEG signals are given in Table 2.

2.3. Classification Schemes

After feature extraction, the classifications were realized using Ensemble Subspace Discriminant (EnsSubDisc) with 5-fold Cross Validation. Ensemble learning improves the performance of known classifiers using random subspace (randomizes the learning over a random subspace), bagging (trains several networks over random data and takes the average of the prediction results), or boosting (changes the weights of several trained networks based on their performance) methods [31]. The signals were classified based on four classification schemes: subject-independent, subject-specific, subject-adaptive, and BCI-dependent.

Subject-Specific: In this classification scheme, the network is trained and tested for each subject using only the same subject's data.

Subject-Independent: Subject-Independent is the scheme where all the data belonging to the subjects except one is used for training. The remaining subject's data is tested using the trained network. This is called the leave-one-subject-out (LOSO) paradigm for evaluation [10].

Subject-Adaptive: In this classification scheme, the data obtained from all the subjects are mixed and separated as train and test sets. Thus, the data is evaluated as a whole, and the performance changes due to subjects can be eliminated. The data are divided randomly, so we used the average results of 5 iterations to generalize the performance of the scheme.

BCI-Dependent: The network is trained using the data belonging to the subject, familiar with a BCI system. The other subjects' data are tested using this trained network. Thus, the effects of BCI familiarity on other subjects can be evaluated.

As it is understood, subject-independent and BCI-dependent classification schemes use transfer learning, meaning that the patterns learned from a subject can be transferred to another [32]. After all the classification schemes were used, the extracted features were analyzed for the best-performed scheme based on the different types of features. The whole feature space was analyzed using a feature selection algorithm called Neighborhood Component Analysis (NCA) to find their ranks based on their effectiveness. NCA changes the feature weights by maximizing the pairwise distance of prediction accuracies and assigning a penalty parameter to all the features causing misclassifications. It is a highly accurate algorithm [33]. The EEG signals were classified using 844, 800, 750, 700, 650, 600, 550, 500, 450, 400, 350, 300, 250, 200, 150, 100, and 50 features based on their rank to find the most effective minimum feature space. The flowchart of the study is given in Figure 2 for a better understanding of the procedure.

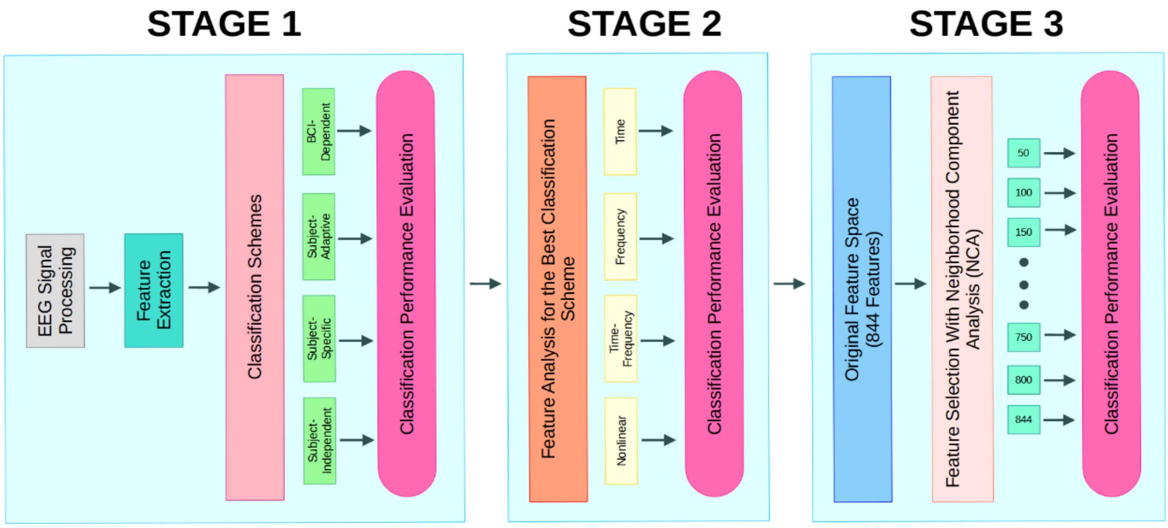

Figure 2 The flowchart of the study indicating the performances of classification schemes and feature selection.

3. RESULTS AND DISCUSSION

The performances of classification schemes are given in Table 3. From the results, it can be surmised that the subject-specific scheme is more accurate than the others for this dataset with %78.3 average accuracy. Interestingly, the third subject's classification results are equivalent to the BCI familiar subject's results. However, when we look at the subject-independent results, it is obvious that a BCI-familiar subject's data can be classified successfully with a network trained with the data of other subjects unfamiliar with a BCI system. A subject-adaptive classification is the next successful classification scheme after subject-specific. Also, the standard deviation is very small for all the iteration results. The BCI-dependent scheme is the least successful one, with an average accuracy of 55.8%. This low accuracy means that the trained network cannot recognize the patterns of the subjects because they are unfamiliar with a BCI system. The samples can be inconsistent. Only the results of the four subjects were used to calculate the average testing accuracy. The first subject's classification result is the trained network's validation performance.

The next procedure was about the effectiveness of the feature types on the classification performance. Thus, we chose the best classification scheme, which is subject-specific.

Table 3 Test accuracies obtained for all the classification schemes. (S1-S5: Subjects, Acc: Accuracy, Std. Dev.: Standard Deviation, Val: Validation)

Classification Scheme	**Test Acc (%) for Each Participant**					**Average Acc (%)**	**Std. Dev.**
	S1	S2	S3	S4	S5		
Subject-Specific	95.7	58.3	95.8	70.8	70.8	78.3	15.0
Subject-Independent	99.5	56.9	58.8	57.5	60.0	66.5	16.5
Subject-Adaptive	72.3	75.9	75.9	71.7	74.1	74.0	1.8
BCI-Dependent	94.7(Val)	60.6	65.0	51.2	46.3	55.8	7.4

Table 4 gives the classification results belonging to different types of features. It is seen from the results that time features are more effective for the first three subjects. Frequency features are the most effective, with an average accuracy of 75.7%. The standard deviation is 5.4, meaning that all subjects have consistent frequency features.

Time-frequency features are especially effective for the first subject and are the second best, with a 73.3% average accuracy. Nonlinear features are the least discriminant features, with a 66.9% average accuracy. However, they are consistent for all subjects with a standard deviation value of 5.0.

Table 4 Test accuracies obtained for all feature types belonging to the subject-specific classification scheme. (S1-S5: Subjects, Acc: Accuracy, Std. Dev.: Standard Deviation)

Feature Type	**Test Acc (%) for Each Participant (Subject-Specific)**					**Average Acc (%)**	**Std. Dev**
	S1	S2	S3	S4	S5		
Time	91.3	68.8	75.0	58.3	50.0	68.7	14.2
Frequency	78.3	66.7	75.0	75.0	83.3	75.7	5.4
Time-Frequency	97.8	68.8	75.0	66.7	58.3	73.3	13.4
Nonlinear	73.9	68.8	70.8	58.3	62.5	66.9	5.0

We determined the effects of feature types on the subject-specific right-hand and left-hand MI EEG classification. Nevertheless, they did not reach the highest accuracy of 78.3% obtained from a subject-specific classification using all the features. Also, it is not enough to evaluate the feature types in themselves. For example, a feature among the nonlinear features can be more effective than one among the frequency features. Thus, we applied the NCA feature selection algorithm to the whole feature space. After determining the ranks of all features, we have classified the signals using 844, 800, 750, 700, 650, 600, 550, 500, 450, 400, 350, 300, 250, 200, 150, 100, and 50 features, to find the most effective minimum feature space. The best classification average accuracy of 80.4% was obtained using 250 features, which can be seen in Figure 3. The results are generally close to each other and over 72% until the classification accuracy drops to 69.1% and 66.1%, with 100 and 50 features, respectively. Table 5 shows the true positive rates and the classification accuracies for all subjects with 250 features. As expected, the best classification accuracy belongs to the BCI familiar subject, while the least classification accuracy belongs to the fourth subject. The more accurate classified direction is the left one, with an 82.1% true positive rate.

Table 5 Classification accuracies and true positive rates of the classes obtained using 250 features found more discriminant after the NCA application. (S1-S5: Subjects, R: Right-direction, L: Left-direction, Acc: Accuracy, Std. Dev.: Standard Deviation)

Classes	**Test Acc (%) for Each Participant (250 Features)**					**Average Acc (%)**	**Std. Dev.**
	S1	**S2**	**S3**	**S4**	**S5**		
R	92.3	69.2	84.6	78.6	66.7	78.3	
L	100.0	86.4	90.9	50.0	83.3	82.1	
Acc	95.7	77.1	87.5	66.7	75.0	80.4	10.1

In Table 6, a comparison of our study with other studies in the literature is given. As seen, the majority of the studies are about the subject-specific scheme. For the subject-specific scheme, in terms of accuracy, our study comes second after [17], which also has the least standard deviation value. Our study has given the best performance with a subject-specific scheme for our dataset, in which the paradigm is not related to any limb movement but movement directions. However, [9], who tried two classification schemes, and [10], who tried three classification schemes, obtained the maximum average accuracies with subject-independent and subject-adaptive schemes, respectively.

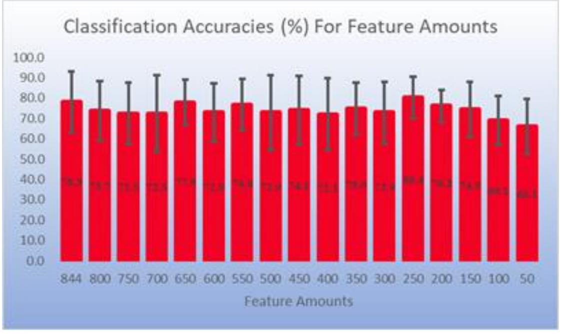

Figure 3 Test accuracies for different amounts of features of which ranks were determined using the feature selection algorithm NCA.

On the other hand, our study is not successful enough with subject-independent and subject-adaptive schemes. On the positive side, our subject-adaptive scheme yielded over 70% accuracy, which the studies in the literature generally obtained, and the standard deviation value is the least among the other studies. The BCI-dependent scheme has the least average accuracy, with 55.8%, but there are no other studies for comparison purposes.

Table 6. Comparison with the other studies in the literature.

Classification Scheme	Study	Method	Average Acc	Std. Dev.
Subject-Specific	[13]	TLCSD	74.9	15.4
	[14]	TSSM-LDA	75.5	13.2
	[15]	FBCSP-CNN	74.5	14.5
	[16]	CSP-RLDA	77.0	12.9
	[4]	CSP-CNN	73.0	-
	[5]	STFT-CNN	74.2	-
	[6]	3D CNN	75.0	7.3
	[7]	STFT-Capsule	77.0	-
	[17]	FAWT-MDS	85.3	3.7
	[18]	MFTL	72.5	10.0
	[8]	ELM	78.5	14.3
	[9]	CNN-Feature Fusion	71.3	15.9
	[10]	CNN	63.5	14.3
	Our Study	EnsSubDisc-NCA	80.4	10.1
Subject-Independent	[9]	CNN-Feature Fusion	74.2	15.8
	[10]	CNN	84.2	10.0
	[11]	EEGSym CNN	84.7	11.7
	[12]	MS-En-CNN	85.4	10.2
	Our Study	EnsSubDisc	66.5	16.5
Subject-Adaptive	[10]	CNN	86.8	11.4
	Our Study	EnsSubDisc	74.0	1.8
BCI-Dependent	Our Study	EnsSubDisc	55.8	7.4

4. CONCLUSION

In this study, we have examined different classification schemes to determine their effects and performances while training networks to classify right-direction and left-direction MI EEG signals. The best classification performance belongs to the subject-specific scheme, unlike in the literature where subject-independent and subject-adaptive schemes were more successful. The minimum feature space was found using NCA with 250 features for maximum accuracy of 80.4%. Our study was most successful using the subject-specific scheme, while the others were not. The subject-adaptive scheme was the next successful one. There are very few studies in the literature that use classification schemes other than the subject-specific scheme. Our study was the first one that uses BCI-dependent classification scheme. The result will be more meaningful if there are more studies about BCI dependency. For a more effective BCI system, more classification schemes must be examined and the studies about other existing classification schemes must be increased. Also, feature spaces can be chosen for each subject separately and simultaneously to create a more adaptive BCI system.

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Authors' Contribution
The authors contributed equally to the study.

The Declaration of Conflict of Interest/ Common Interest
No conflict of interest or common interest has been declared by the authors.

The Declaration of Ethics Committee Approval
For the data used in the study, the approval of the Ethics Committee of Selcuk University Faculty of Medicine was obtained with the decision numbered 2020/146 by applying to the Noninvasive Clinical Research Ethics Committee.

The Declaration of Research and Publication Ethics
The authors of the paper declare that they comply with the scientific, ethical and quotation rules of SAUJS in all processes of the paper and that they do not make any falsification on the data collected. In addition, they declare that Sakarya University Journal of Science and its editorial board have no responsibility for any ethical violations that may be encountered, and that this study has not been evaluated in any academic publication environment other than Sakarya University Journal of Science.

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